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Computational Intelligence Applications for Defense

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This report reviews the priorities and discusses cognitive algorithms resulting in breakthroughs in defense applications, and making progress toward achieving AF goals. The mathematical techniques of dynamic logic and neural modeling fields model aspects of the functionality of the mind: perception, cognition, and higher cognitive functions. This leads to a significant improvement in classical signal processing applications, including detection, tracking, and fusion in noise and clutter, making autonomous situational awareness possible. The first part of this report describes past difficulties, why these problems have not been solved for decades, and the gist of the current approaches. The second part of this report addresses future research directions: the augmentation of human performance through improvements in man-machine interfaces. This includes modeling of language interacting with cognition. In future systems, computers will learn from humans, and humans will operate machines by language and thoughts..

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1. Introduction

Every decade the Department of Defense determines its technical challenges for the next 10 to 20 years. The top Air Force (AF) priorities identified in 2010 allocate a prominent role to computational intelligence. This article reviews those priorities and discusses cognitive algorithms resulting in breakthroughs in defense applications, and making progress toward achieving the AF goals. The mathematical techniques of dynamic logic and neural modeling fields model aspects of the functionality of the mind: perception, cognition, and higher cognitive functions. This leads to a significant improvement in classical signal processing applications, including detection, tracking, and fusion in noise and clutter, making autonomous situational awareness possible. The first part of this paper describes past difficulties, why these problems have not been solved for decades, and the gist of the current approaches. The second part of this paper addresses future research directions: the augmentation of human performance through improvements in man-machine interfaces. This includes modeling of language interacting with cognition. In future systems, computers will learn from humans, and humans will operate machines by language and thoughts.

The 2010 report “Technical Horizons” by the Chief Scientist of the US Air Force analyzes many details of the technical challenges faced by the Air Force over the next 20 years [1]. Among three most essential focus areas, the first two identify a need for autonomous systems and augmentation of human performance. The most important technologies include the need for processing of the overwhelming amount of signals collected by diverse sensors.

The brain works better than computers. Therefore, computational intelligence attempts to model brain mechanisms and to apply these models to developing cognitive algorithms, which would bring computer system performance closer to the performance of the brain-mind [2].

These attempts began in the 1950s, and the first designers of computational intelligence were sure that soon computers would overtake human intelligence. Yet modeling the brain-mind turned out to be much more challenging than expected. Computers still cannot do what is easily done by children and animals. The Chief Scientist of the Air Force has identified the improving of computer abilities as the most important technical horizon for USAF research over the time span 2010-30. Section II discusses specific mathematical reasons, which made computational intelligence a far more difficult problem than originally expected. We also touch on fundamental psychological mechanisms that have diverted outstanding scientists from looking in promising directions to solve these problems.

Experimental neuroimaging and cognitive neuroscience discovered several fundamental principles of the brain-mind organization. Among these are interactions between bottom-up and top-down signals [3,4,5,6], a theory of instincts and emotions [7], the knowledge instinct and aesthetic emotions [8,9,10,11,12,13] extending the previous reference [7] to higher cognitive functions, and to mechanisms of "vague-to crisp" transformation of initially vague and unconscious states of top-down projections [14]. Section III describes these experimental findings, mathematical models of these processes, dynamic logic (DL), neural modeling fields (NMF), and their fundamental role in overcoming past difficulties as discussed in the previous section.

Section IV describes applications of DL-NMF to classical signal processing problems, detection, tracking, and fusion of sensor signals from multiple platforms in strong clutter. These problems have not been solved for decades. Also autonomous learning of situations is addressed, which is a problem of the next level of complexity. Section V addresses an emerging engineering problem of learning language, and interaction between language and cognition. This is crucial for the augmentation of human performance through the improvement of the human-computer interactions. Section VI discusses future research and development directions.

2. Past difficulties: complexity and logic

The perception and cognition abilities of computers still cannot compete with those of kids and animals [15]. Most algorithms and neural networks suggested since the 1950s for modeling perception and cognition, as discussed in [16,17,18,19], faced the difficulty of combinatorial complexity (CC). Rule systems of artificial intelligence in the presence of variability have grown in complexity: rules have become contingent on other rules, and rule systems faced CC. Learning algorithms and neural networks have to be trained to understand not only individual objects, but also combinations of objects, and thus, faced CC of training. Fuzzy systems required a fuzziness level to be set appropriately in different parts of the systems, also degrees of fuzziness vary in time, and attempts to select efficient levels of fuzziness would lead to CC.

These CC difficulties were related to Gödelian limitations of logic; they were manifestations of logic inconsistency in finite systems [8,20]. Even approaches designed specifically to overcome logic limitations, such as fuzzy logic and neural networks, encountered logical steps in their operations: neural networks are trained using logical procedures (e.g. "this is a chair"), and fuzzy systems required logical selection of the degree of fuzziness.

Millennia logic was associated with the essence of mind mechanisms. Near the beginning of the 20th century, Hilbert was sure that his logical theory also described the mechanisms of the mind: "The fundamental idea of my proof theory is none other than to describe the activity of our understanding, to make a protocol of the rules according to which our thinking actually proceeds" [21]. This vision of logic modeling the mind was shattered by Gödel's discoveries in the 1930s [22]. But why 25 years after Gödel, in the 1950s, where the founders of artificial intelligence sure that logic is adequate for modeling of the mind?

The reason for the fascination by logic is fundamental to science, engineering, and related to the mechanisms of the mind was only understood recently [4,8,14,23]. Most of the mind's mechanisms are usually inaccessible to consciousness, e.g., we are not conscious about the individual neural firings and intermediate signal processing steps. Only the "final results" of perception and cognition, nearly crisp logic-like perceptions and thoughts, are available to consciousness. These "final results" approximately obey the rules of logic. Logical conscious states are like islands in the ocean of unconsciousness. But in our consciousness there are only crisp logical results, and consciousness works so that, while jumping through oceans of unconsciousness, we subjectively feel as if we smoothly flow from one conscious logical state to the next. Our intuitions about the mind, including scientific intuitions are strongly biased towards logic. This is why, most algorithms and neural networks (even if purposefully designed to oppose logic) use logic in a fundamental way. Due to scientific findings we know today that logic is not a fundamental mechanism of the mind.

3. Cognitive mechanisms: mathematical models and experimental evidence

Cognitive, neurological and neuroimaging studies [6,8,14] demonstrated that the mind understands the world by modeling it. Here the word "model" is used in two distinct meanings. First, the mind models the world; second, the article describes mathematical processes that model these mechanisms of the mind. So we talk about mental models of the world and mathematical models of the mind. The mind models the world using mental representations, or models of the world. Consider a simplified process of visual perception. To perceive an object, a mental representation of this object in our memory should be matched to patterns in sensor signals corresponding to the object. During this matching process, the retina projects sensor

signals onto the visual cortex; these projections are called *bottom-up* signals. In parallel, object representations in memory (mental models) send *top-down* signals (projections) to the visual cortex [4,8,14]. The mind is organized in a multi-level, approximately-hierarchical structure. Higher level cognition involves higher levels; matching bottom-up and top-down signals between adjacent levels is the mechanism of cognition.

Neuroimaging studies [14] have demonstrated that conscious perceptions are *preceded* by activation of cortex areas, where the top-down signals originate. Experiments also demonstrated that the initial top-down projections are *vague and unconscious* (or less conscious) than perceptions of objects at the end of the matching process. As discussed in this article, these mechanisms are fundamental for the functioning of the mind; they enable the mind to overcome difficulties of the mathematical models discussed in the previous sections [8,24,25,26]. The mathematical models of the mind mechanisms help in understanding properties of the mind that previously seemed mysterious. They also lead to cognitive algorithms, which significantly outperform the previous state of the art [8]. Mathematical models of these processes, dynamic logic (DL) and neural modeling fields (NMF) are discussed below.

NMF mathematically describes multi-level, approximately-hierarchical structure of the mind [8] discussed above. At each level in NMF, there are mathematical models of mental representations, $\mathbf{M}(m)$ (called *models*, m = 1,… M) and mathematical description of the matching process. Representations, $\mathbf{M}(m)$, encapsulate the mind's knowledge. As discussed, they generate top-down neural signals, interacting with bottom-up signals, $\mathbf{X}(n)$. Models $\mathbf{M}(m)$ predict patterns in signals $\mathbf{X}(n)$, which correspond to object m. They depend on parameters, $\mathbf{S}_m$, characterizing a particular view of the object m (distance, angles, lightings, etc.). Interactions between signals are governed by the knowledge instinct, which drives the matching of bottom-up and top-down signals. In this matching process, multiple vague models compete with each other and are modified for better matching patterns in bottom-up signals. This constitutes learning,

adaptation, and if needed, formation of new models for better correspondence to the input signals.

A mathematical model of the knowledge instinct is described as maximization of a similarity measure, L, between bottom-up and top-down signals, [8,17].

$$L = \prod_{n \in N} \ell(\mathbf{X}(n)); \;\; \ell(\mathbf{X}(n)) = \sum_{m \in M} r(m)\, \ell(\mathbf{X}(n) \mid \mathbf{M}(m)). \quad (1)$$

Here, $\ell(\mathbf{X}(n) \mid \mathbf{M}(m))$ or $\ell(n|m)$ for shortness is a similarity of signal, $\mathbf{X}(n)$, "conditional" on object m being present, [8]. Therefore, when combining these quantities into the overall similarity measure, L, they are multiplied by rates r(m), which represent a probabilistic measure of object m actually being present; rates, r(m), are unknown parameters along with $\mathbf{S}_m$.

The learning, or matching bottom-up and top-down signals, consists of associating signals, n, with concepts, m, and estimating model parameters, $\mathbf{S}$, by maximizing similarity L. Note that all possible combinations of signals and models are accounted for in similarity (1). This can be seen by expanding a sum in (1), and multiplying all the terms which would result in a huge number of M^N items. This is the number of combinations between all signals, N, and all models, M. Here is the source of CC of many algorithms used in the past. NMF solves this problem by using dynamic logic (DL) [17,20]. An important aspect of DL is matching vagueness or fuzziness of similarity measures to the uncertainty of models. Initially, parameter values are not known, and uncertainty of the models is high; so is the fuzziness of the similarity measures. In the process of learning, the models become more accurate, the similarity measure more crisp and the value of the similarity increases. This is the mechanism of DL.

Mathematically it is described as follows. First, assign any values to unknown parameters, $\mathbf{S}_m$. Then, compute association variables f(m|n),

$$f(m|n) = r(m)\,\ell(n|m) \Big/ \sum_{m' \in M} r(m')\,\ell(\mathbf{X}(n)|m'). \tag{2}$$

DL is defined as follows,

$$d\mathbf{S}_m/dt = \sum_{n \in N} f(m|n)[\partial \ln \ell(n|m)/\partial \mathbf{M}_m]\partial \mathbf{M}_m/\partial \mathbf{S}_m\,, \tag{3}$$

Parameter t is the time of the internal dynamics of the NMF system, like a number of iterations, if solving (3) by iterative steps. On every iteration, new values of parameters are substituted in eq.(2). The above procedure has been proven to converge [8]. Local maxima are avoided due to DL beginning with vague similarity measures, which smooth local maxima over [25,27,23]. This process "from vague to crisp" is the essence of DL. Various possible neural mechanisms of DL in the brain are discussed in [28,29,30].

4. Applications of DL-NMF to classical previously unsolved problems

NMF-DL was applied to a number of complicated problems fundamental for defense applications in signal processing, detection, and clustering problems [8,9,23,27,31,32,33,34,35, 36,37,38], which could not have been solved previously because of strong clutter interfering with signals. Obtained solutions often approach information-theoretic performance bounds and therefore are the best possible [39,40,41,42,43]. Here, we briefly illustrate three problems: detection, tracking, fusion in strong clutter [44,45,46,47,48]. We also describe a solution to a longstanding unsolved problem of autonomous situational awareness.

In the first example, NMF-DL is detecting ‘smile’ and ‘frown’ patterns in noise shown in Fig.1a without clutter, and in Fig.1b with clutter, as actually measured [233]. This example is beyond the capabilities of previously existing techniques because of the computational complexity. The DL complexity in this example is equal 10^9, so that a problem, previously unsolvable due to complexity, has been solved using NMF-DL.

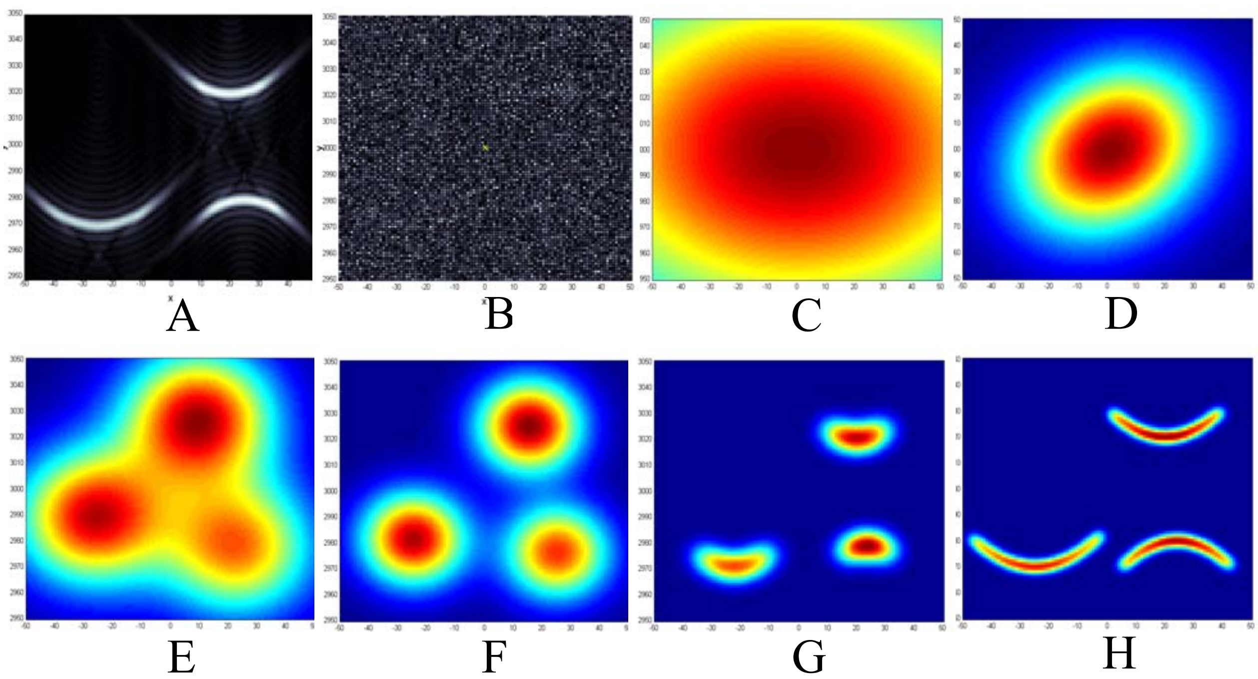


Fig.1. An example of NMF-DL perception of ‘smile’ and ‘frown’ objects in clutter in 2-dimensional space: (a) true ‘smile’ and ‘frown’ patterns are shown without clutter; (b) actual image available for recognition (signal is below clutter, S/C ~ 0.5); (c) an initial fuzzy blob-model, the fuzziness corresponds to uncertainty of knowledge; (d) through (h) show improved models at various iteration stages (total of 22 iterations). The improvement over the previous state of the art is 7,000% in S/C.

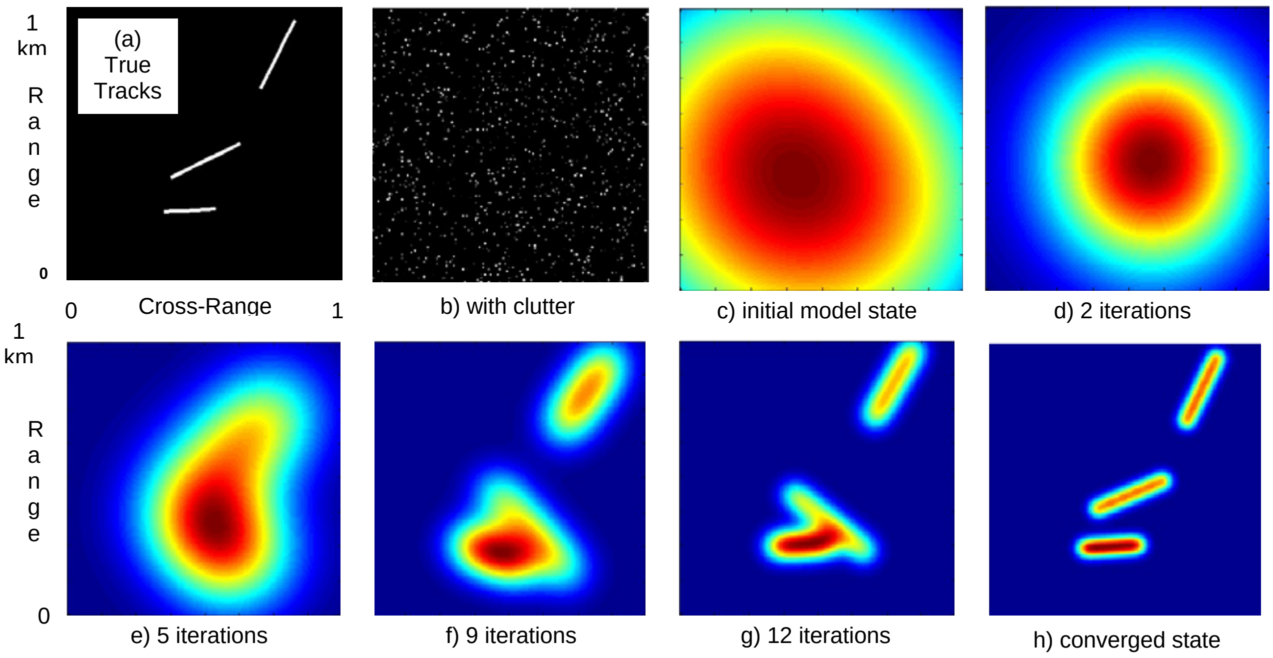


Fig. 2. Joint detection and tracking of objects below clutter using NMF-DL: (a) true track positions in 1 km x 1 km data set; (b) actual data available for detection and tracking. Evolution of the NMF-DL is illustrated in (c)–(h), where (c) shows the initial, uncertain model and (h) shows the model upon convergence after 20 iterations. Converged models are close to the truth (a).

The second example, Fig. 2, shows NMF-DL joint detection and tracking of targets below clutter. The third axis, time, is perpendicular to the page; 6 time scans are shown collapsed on top of each other, details of this example are discussed in [27]. In this example, targets cannot be detected on a single scan, therefore detection and tracking have to be performed simultaneously ("track before detect"); in terms of S/C ratio the improvement is approximately 8,000%.

The third example, Fig.3, shows NMF-DL joint detection, tracking, and fusion of sensors from three platforms [38]. Fig.3 shows 1 scan from each sensor and several DL iterations. In this case, because of low signal to clutter ratio, S/C, targets cannot be detected from a single sensor, therefore, joint fusion, tracking, and detection have to be performed concurrently. In addition,

GPS does not give enough accuracy for triangulation, therefore, relative target localization has to be performed concurrently with other processing. Problems of this complexity have not been previously solved.

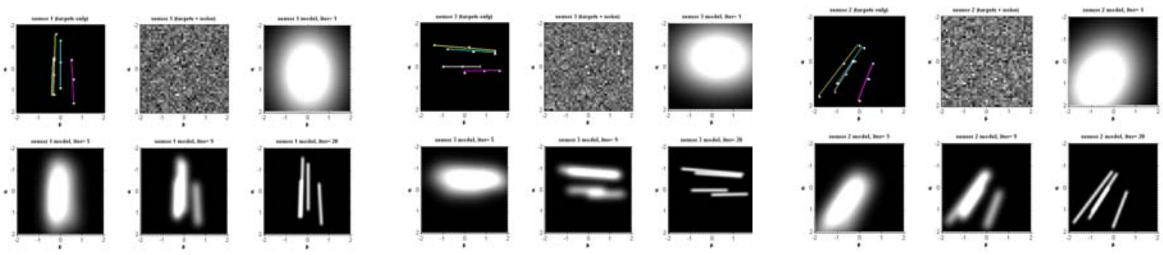
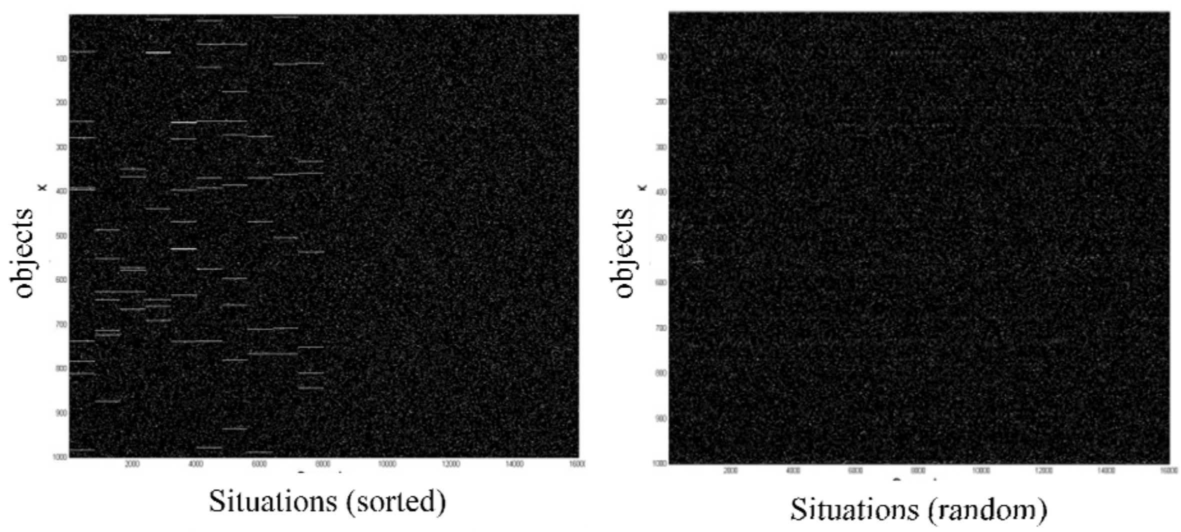


Fig.3.1, sensor 1 Fig.3.2, sensor 2 Fig.3.3, sensor 3

Fig.3. Illustrates NMF-DL joint detection, tracking, and fusion of sensors from 3 platforms. The figure shows for each sensor: four true tracks, 1 scan, where targets are not seen under clutter, and several iterations of DL. In this case targets cannot be detected from a single sensor, therefore joint fusion, tracking, and detection have to be performed concurrently. In addition, GPS does not give enough accuracy for triangulation, therefore, relative target localization has to be performed concurrently with other processing.

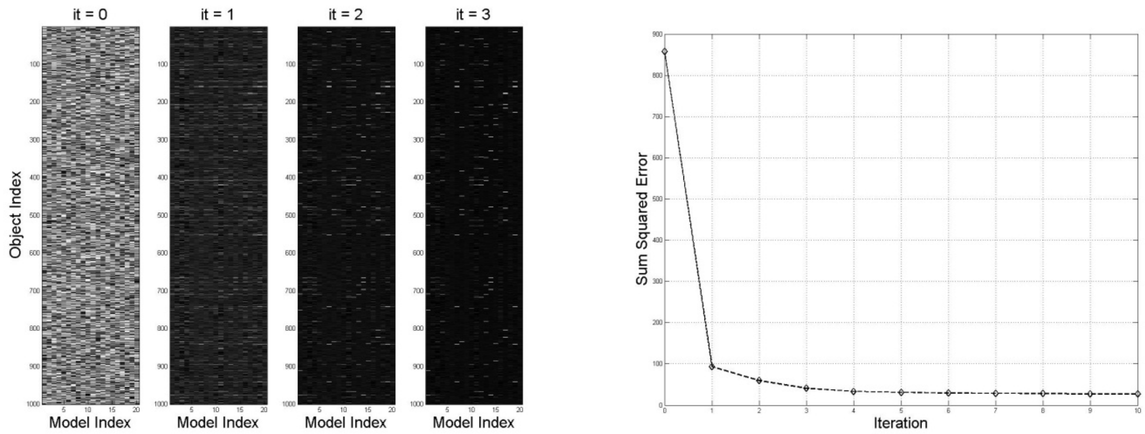
The fourth example, Figs. 4 through 6, illustrates autonomous learning of situations, a problem of the next level of complexity comparative to the previously considered. Autonomous learning of situations was recognized as an important military problem for decades, however it was not solved. It is difficult because every situation contains several objects relevant to this particular situation, and a large number of irrelevant objects. The data are shown in Fig. 4.



a b

Fig. 4. Learning situations; white dots show present objects and black dots correspond to absent objects. Vertical axes show 1000 objects, horizontal axes show 10 situations each containing 10 relevant objects and 40 random ones; in addition there 5000 "clutter" situations containing only random objects. Fig. 4a shows situations sorted along horizontal axis, hence there horizontal lines corresponding to relevant objects (the right half contains only random noise). Fig 4b shows the same situations in random order, which looks like random noise.

In real life, situations are often coming in random order, without a teacher pointing to a particular object indicating situations like in Fig. 4b. To find situations, say by sorting along horizontal axes, until horizontal lines appear as in Fig. 4a, would take about M^N operations; assuming, say, M=20 situations, the number of operations is ~ 10^{13000}. NMF-DL solves the problem as described in [49,50]. The solution and the low level of errors are illustrated in Fig. 5. Fig. 5a illustrates DL iterations beginning with random association of objects and (arbitrary taken) 20 situations. Fig. 5b illustrate that errors quickly go to a small value. After the problem of associating objects and situations are solved by using DL, the correct situations are chosen by matching to the known data. The error does not go to 0 for numerical reasons as discussed in [50].



a b

Figure 5. (a) shows DL initiation (random) and the first three iterations (Fig. 5a); the vertical axis shows objects and the horizontal axis shows models (from 1 to 20). The problem is approximately solved by the third iteration. This is illustrated in Fig 5b, where the error is shown on the vertical error. The correct situations are chosen by minimizing the error. The error does not go to 0 for numerical reasons as discussed in [50].

In the above example, relationships (such as on-the-left-of, or under) have not been explicitly considered. They can be easily included. Every relation and object can include a marker, pointing what relates to what. These markers are learned the same way as objects [49,50].

Solving problems like detection, tracking, and fusion require models matching the problem, which is described in the given references. The problem of learning situations is a general one, it is appropriate for matching the bottom-up and top-down signals at every level in the approximate hierarchy of the mind. Following sections describe how it can be applied to solving new emerging class of engineering problems, including interaction between language and cognition.

5. Cognition and language

As discussed, augmentation of human performance by computers has been identified by the AF as a top priority. This goal faces the bottleneck of the human-machine interface [51,52]. Overcoming this bottleneck is possible by mathematically modeling interaction between language and cognition [53,54,24]. Before attempting mathematical modeling of language, one needs to understand why previous decades of research in this direction have not succeeded. Therefore, this section begins with the mysteries facing this problem so far, and how cognitive computational intelligence building on NMF-DL promises to resolve them. These mysteries include the following: In what way is language and cognition similar and different? Do we think with words? Or do we use words for communicating completed thoughts? Why children learn language by 5 years of age and can talk practically about the entire contents of culture, but cannot act like adults? Why are there no animals thinking like humans and speaking no human-like language?

Consider first how is it possible to learn which words correspond to which objects? Contemporary psycholinguists follow the ancient Locke idea, Associationsim: associations between words and object are just remembered. But this is mathematically impossible. The number of combinations among 100 words and 100 objects is larger than all the elementary particle interactions in the Universe. Combinations of 30,000 words and objects are practically infinite. Mathematical linguists did not offer any solution. NMF-DL solves this problem using the dual model [55,56,57]. Every mental representation consists of a pair of two models, or two model aspects, cognitive and language. Mathematically, every concept-model $\mathbf{M}_m$ has two parts, linguistic $\mathbf{ML}_m$ and cognitive $\mathbf{MC}_m$:

$$\mathbf{M}_m = \{ \mathbf{ML}_m, \mathbf{MC}_m \}; \tag{4}$$

This dual-model equation suggests that the connection between language and cognitive models is inborn. In a newborn's mind, both types of models are vague placeholders for future cognitive and language contents. An image, say of a chair, and the sound "chair," do not exist in a newborn's mind. But the neural connections between the two types of models are inborn; therefore the brain does not have to learn associations between words and objects - which concrete word goes with which concrete object. Models acquire specific contents in the process of growing up and learning, linguistic and cognitive contents are always staying properly connected. Zillions of combinations need not be considered. The initial implementations of these ideas lead to encouraging results [58,59,60,61,62,63].

Consider language hierarchy higher up from words, Fig. 6. Phrases are made up from words similar to situations made up from objects. Because of the linear structure, language actually is simpler than situations; rules of syntax can be learned similar to learning objects and relations using markers, as described in the previous section. The reason computers do not speak English used to be the fundamental problem of combinatorial complexity. Now that the fundamental problem is solved, learning language will be solved in due course. Significant effort will be required to build machines learning language. However, the principal difficulty has been solved in the previous section. The mathematical model of learning situations, considered in the previous section, is similar to learning how phrases are composed from words. Syntax can be learned similar to relations between objects [49,50,64].

The next step beyond current mathematical linguistics is modeling the interaction between language and cognition. It is fundamental because cognition cannot be learned without language. Consider a widely-held belief that cognition *can* be learned from experience in the world. This belief is naïve and mathematically untenable. The reason is that abstract concepts-

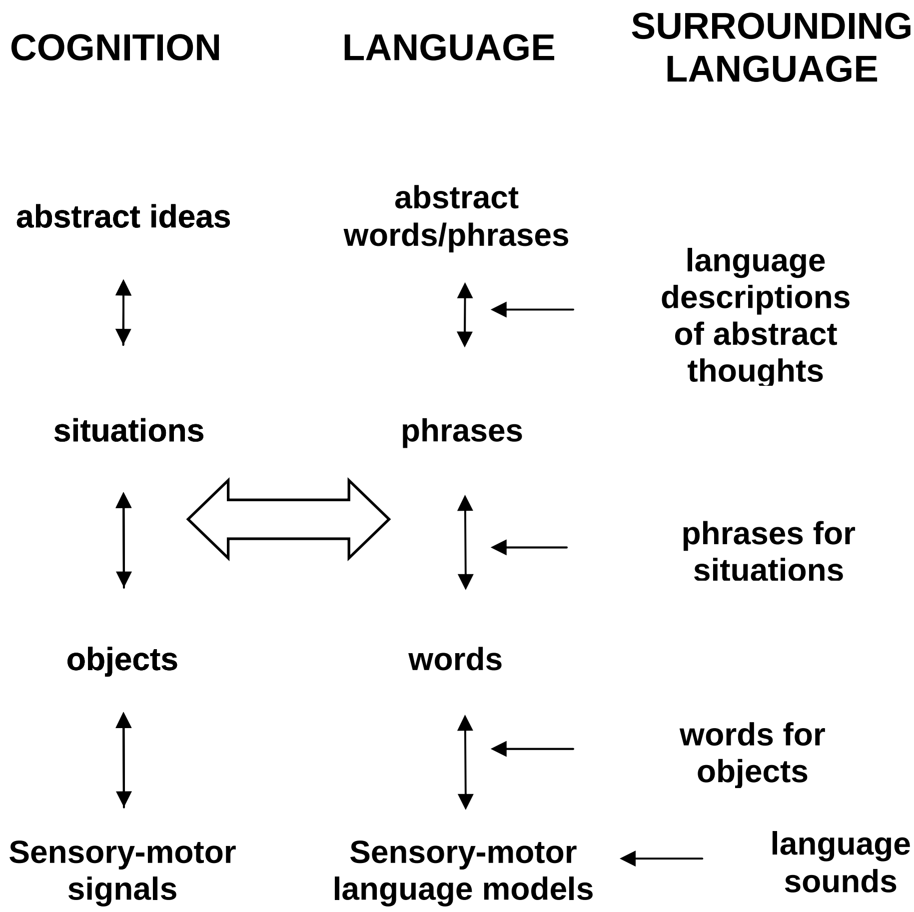


Fig. 6. Parallel hierarchies of language and cognition consist of lower level concepts (like situations consist of objects). A set of objects (or lower level concepts) relevant to a situation (or higher level concept) should be learned among practically infinite number of possible random subsets (as discussed, larger than the Universe). No amount of experience would be sufficient for learning useful subsets from random ones. The previous section overcame combinatorial complexity of *learning*, given that the sufficient *information* is present. However, mathematical linguistic theories offer no explanation where this information would come from.

representations consist of a set of relevant bottom-up signals, which should be learned from a practically infinite number of possible random subsets (as discussed, a number larger than particles in the Universe). No amount of experience would be sufficient for learning useful subsets from random ones. The previous section overcame combinatorial complexity of learning,

given that the sufficient information is present. However, mathematical linguistic theories offer no explanation where this information would come from.

NMF-DL with dual model and dual hierarchy suggests that information is coming from language. This is the reason why no animal without human-type language can achieve human-level cognition. This is the reason why humans learn language early in life, but learning cognition (making cognitive representations-models as crisp and conscious as language ones) takes a lifetime. Information for learning language is coming from the surrounding language at all levels of the hierarchy. Language model-representations exist in the surrounding language 'ready-made.' Learning language is thus grounded in the surrounding language.

For this reason, language models become less vague and more specific by 5 years of age, and much faster than the corresponding cognitive models for the reason that they are acquired ready-made from the surrounding language. This is especially true about the contents of abstract models, which cannot be directly perceived by the senses, such as "law," "abstractness," "rationality," etc. While language models are acquired ready-made from the surrounding language, cognitive models remain vague and gradually acquire more concrete contents throughout life guided by experience and language. According to the dual-model, this is an important aspect of the mechanism of what is colloquially called the "acquiring experience."

Human learning of cognitive models continues throughout the lifetime and is guided by language models. If we imagine a familiar object with closed eyes, this imagination is not as clear and conscious as perception with opened eyes. With opened eyes, it is virtually impossible to remember imaginations. Language plays the role of eyes for abstract thoughts. On one hand, abstract thoughts are only possible due to language, on the other, language "blinds" our mind to the vagueness of abstract thoughts. Whenever one talks about an abstract topic, he (or she) might think that the thought is clear and conscious in his (or her) mind. But the above discussion suggests that we are conscious about the *language* models of the dual hierarchy. The cognitive

models in most cases may remain vague and unconscious. During conversations and thoughts, the mind smoothly glides among language and cognitive models, using those that are more crisp and conscious – 'more available.' Scientists, engineers, and creative people in general are trained to differentiate between their own thoughts and what they read in a book or paper, but usually people do not consciously notice if they use representations acquired from personal experiences and deep thoughts, or from what they have read or heard from teachers or peers. The higher up in the hierarchy the more vague the contents of abstract cognitive representations are, while due to the crispness of language models we may remain convinced that these are our own clear conscious thoughts.

Another mystery of human-cognition, which is not addressed by current mathematical linguistics, is basic human irrationality. This has been widely discussed and experimentally demonstrated after discoveries of Tversky and Kahneman [65], leading to the 2002 Nobel Prize, According to NMF-DL, it originates from the discussed dichotomy between cognition and language. Language is crisp in the human brain, while cognition might be vague. Yet, collective wisdom accumulated in language may not be properly adapted to one's personal circumstances, and therefore be irrational in a concrete situation. In the 12th century Maimonides wrote that Adam was expelled from paradise because he refused original thinking using his own cognitive models, but ate from the tree of knowledge and acquired collective wisdom of language [66].

The dual-model also suggests that the inborn neural connection between cognitive brain modules and language brain modules (evolving over thousands or millions of years of evolution) is sufficient to set humans on an evolutionary path separating us from the animal kingdom. Neural connections between these parts of cortex existed for millions of years ago due to mirror neuron system, what Arbib called the "language prewired brain" [67].

The combination of NMF-DL and the dual model and hierarchy introduces new mechanisms of language and its interaction with cognition. These mechanisms suggest solutions

to a number of psycholinguistic mysteries, which have not been addressed by mathematical linguistics. These include fundamental cognitive interaction between cognition and language, similarities and differences between these two mechanisms; word-object associations; why children learn language early in life, but cognition is acquired much later; why animals without human language cannot think like humans. These mechanisms connected language cognition dichotomy to 'irrationality' of the mind discovered by Tversky-Kahneman, and to the story of the Fall and Original sin.

The mathematical mechanisms of NMF-DL-dual model are relatively simple and follow eqs. (2) through (4), also see details in the given references. These mathematical mechanisms correspond to the known structure and experimental data about the brain-mind. In addition to conceptual mechanisms of cognition, they also describe emotional mechanisms and their fundamental role in cognition and world understanding, including role of aesthetic emotions, beautiful, sublime, and musical emotions [68,69,70]. Based on these foundations future defense applications of cultural models will be developed.

6. Conclusions

Computational intelligence is destined to play the most important role in defense applications for decades to come. Its role is to augment human performance and to automate as much as possible complex problems of analyzing overwhelming amounts of sensor data coming from a variety of sources. To achieve this role, cognitive algorithms modeling the performance of the human mind are being developed. This requires the discovery and modeling the fundamental "first principles" of the mind operations. Several first principles of the mind-brain organization have been identified by a number of researchers in the given references, described

and mathematically modeled in this article. This is leading to a significant improvement in solving classical engineering problems. Let us summarize these mechanisms here: instincts, emotions, concepts; bottom-up and top-down neural signals interacting through a vague-to-crisp process; the knowledge instincts and aesthetic emotions governing this interaction. These mechanisms are shared with higher animals. Human level cognition requires human language. The only additional required mechanism, it seems, is the dual model, leading to the dual hierarchy of language and cognition. Future development in this direction will lead to cooperative man-machine systems.

To achieve this and develop cooperative human-machine defense applications augmenting human performance at the level of human-level cognition, the mechanism of joint language and cognition described above should be implemented in a multi-agent system, where each agent would possess the dual language-cognition NMF-DL model. Simulations should demonstrate learning hierarchical language from human language, and then learning hierarchical cognition from sensor data, and guided by language. The next step will implement this intelligent multi-agent hierarchical system in cooperative man-machine systems, where computers will learn from humans and then augment human performance. The described mathematical approach also will be extended 'below' objects to creating object-recognition systems where objects will be modeled as 'situations' of sensory features. Similarly, speech will be modeled by linear 'situations' of sounds.

Another approach to human performance augmentation by computers will exploit direct connection between cognitive states of the mind and computers. Cognitive states of the mind will be sensed by EEG sensor arrays. The difficulty of this approach is due to noisy contents of EEG signals. New cognitive algorithms will overcome this difficulty similar to Fig. 1, as discussed in [71].

An important defense application is cultural intelligence, which potentially will lead to improved cultural understanding, improved collaborations of diverse cultures, reduced conflicts and casualties. Extending the models of language, cognition, and emotions to developing predictive cultural models might be among the most important emerging engineering directions in the 21st century. Initial models developed in [72,73,74,75] promise explanation and prediction of cultural phenomena currently threatening world peace. Improved models will help better intercultural understanding and achieving peace in the current complicated multi-cultural global environment.

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